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Spot price forecasting for best trading strategy decision support in the Iberian electricity market

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A R T I C L E I N F O

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A B S T R A C T

The increasing volatility in electricity markets has reinforced the need for better trading strategies by both sellers and buyers to limit the exposure to losses. Accordingly, this paper proposes an electricity trading strategy based on a mid-term forecast of the average spot price and a risk premium analysis based on this forecast. This strategy can help traders (buyers and sellers) decide whether to trade in the futures market (of varying monthly maturity) or to wait and trade in the spot market. The forecast model consists of an Artificial Neural Network trained with the Long Short Term Memory architecture to predict the average monthly spot prices, using only market price-related data as input variables. Statistical analysis verified the correlation and dependency between variables. The forecast model was trained, validated and tested with price data from the Iberian Electricity Market (MIBEL), in particular the Spanish zone, between January 2015 and August 2019. The last year of this period was reserved for testing the performance of the proposed forecast model and trading strategy. For comparison purposes, the results of a forecasting model trained with the Extreme Learning Machine over the same period are also presented. In addition, the forecasted value of the average monthly spot price was used to perform a risk premium analysis. The results were promising, as they indicated benefits for traders adopting the proposed trading strategy, proving the potential of the forecast model and the risk premium analysis based on this forecast.

1. Introduction

Electricity consumption is increasingly integrated into everyone's life, revealing a strong causal relation with economic activity (Albuquerque et al., 2022). The International Energy Agency projects that this trend will only be accentuated in the future, with the steady electrification of societies and the consumption of energy that will be increasingly generated by non-polluting technologies. Over the next two years, the average annual electricity demand is expected to grow 2.7%. Although the Covid-19 pandemic and high energy prices add uncertainty to this estimate, this moderate growth in demand is almost matched by the growth of renewable energy production (Agency, 2022). Thus, the price of electricity is a very important element for society, with a profound impact on the budgets of domestic users, businesses and industry, i.e., highlighting the social value of electricity (Roy, 2020).

The liberalization of electricity markets in EU countries, in the early 2000s, was a very important step for the energy industry, which transitioned from a monopolistic framework to a more competitive and transparent market, with the final goal of achieving an EU-wide integrated energy market (Pepermans, 2018; Vasilica Rotaru, 2013).

In Portugal and Spain, electricity can be traded, i.e., bought or sold, in the multinational Iberian Electricity Market (MIBEL), which began its operation in 2007 (Estevão & Raposo, 2018). Trading on MIBEL is done in a liberalized but structured manner, where traders can buy and sell under a series of different contracting formats, among them: (i) *Spot market*, divided into day-ahead and intraday markets. The spot market follows a single marginal price model, wherein all buyers pay the same price and all sellers receive the same price. As the spot market includes both Portugal and Spain, the system foresees possible mismatches between cross-border offers and the interconnection capacities, that represent the commercially available energy-flow between the two countries. Whenever this occurs, the current rules determine that the

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two market zones – corresponding to Portugal (PTEL) and Spain (SPEL) – be separated and specific prices must be found for each of these areas, a mechanism known as “market splitting”. This market is managed by the Iberian Energy Market Operator (OMIE) – Spanish Pole (OMIE, 2022). (ii) *Forward market*, a regulated market that offers a trading platform for energy derivatives, namely Futures, Forwards, Swaps and Options. The most common trade involves futures contracts, an agreement to trade energy, with a given maturity in the future (day, week, weekend, month, quarter and year), wherein the buyer purchases electricity within a delivery period and the seller provides that electricity at a price determined at the time of the transaction. This contract has daily settlements (margins) between the transaction price and the market quotation (futures) of each day. The buying and selling agents do not have a direct relationship with each other, and the clearing house is responsible for settling the daily margins and the contract on the delivery date or period. This market is managed by the Iberian Energy Market Operator (OMIP) – Portuguese Pole (OMIP, 2022).

1.1. Literature review: trading strategies

The management and pricing of this Iberian market have been constantly refined as a result of operational experience, the application of EU legislation and, significantly, the effects of a revolution in renewable energy. This sector is considered a priority but is inherently unpredictable (Bento et al., 2022). In this regard, Iberian countries are leaders in renewable capacity integration, i.e. the annual share of renewable energies in these countries can surpass that of non-renewables (Bento et al., 2021), mainly due to a strong investment in wind power. However, this contributes to high levels of price volatility (Masoumzadeh, 2018) and implies significant challenges for operators within this liberalized electricity market.

Given the uncertain nature of this market, price and volatility forecasting are crucial (Kara et al., 2021). Understanding pricing in electricity forward markets, and hence electricity risk premia, is of the utmost importance for market players, allowing them to gauge trading strategies (Jacobs et al., 2022). For instance, authors in (Pinto et al., 2016) presented a system for MIBEL agents, indicating the best market strategy based on spot price forecasts. To ascertain the best trading strategy, (Lopes, 2018; Santos et al., 2016) developed simulation methods for the same electricity market. A recent work (Teixeira et al., 2021) presented an intelligent model for spot price forecasting and a tool to make trading decisions that consider the risk of exposure to spot market volatility, thus improving the electricity purchase decision process; MIBEL was explored as a case study. In another example, a risk management strategy for electricity spot exposures using futures hedging is validated in 3 different European electricity markets, proofing that in certain periods, hedging strategies can be very successful, in particular for longer horizons (Hanly et al., 2018).

To sum up, in an environment increasingly dominated by high renewable energy penetrations, distributed facilities, advanced metering, and consumer awareness it is necessary for market participants, to adopt innovative decision-making methods that can mitigate the overall risk (Yang et al., 2018). Consequently, recognizing the complexity of the price dynamics, as well as the multiplicity of market options for traders, there is a gap for the use of accomplished machine learning (ML) models (Hameed et al., 2021) to accomplish those objectives.

1.2. Contributions

The main contributions of this paper can be summarized as follows: i) a trading strategy that supports traders make the best choice between trading electricity in the futures market or waiting in the spot market is developed and tested using real data from the Iberian electricity market; ii) an alternative and clearer formulation of ex post risk premium, capable of identifying bad decisions; (iii) a forecasting model based on a Long Short-Term Memory network trained with a tailored input dataset, showing significant error improvements in comparison with a set of benchmark forecast models; (iv) an analysis of the cost and profit of traders based on the decision recommended by the risk premium calculation, proving the efficiency of both the forecast model and the proposed trading strategy in a comprehensive scenario.

1.3. Paper structure

The paper is organized as follows: Section 2 presents the proposed forecast model and the variables used in this study, accompanied by a brief statistical analysis, as well as the trading strategy for market agents; Section 3 provides the results and discussion of a case study on MIBEL for both buyers and sellers in the established period; and lastly, Section 4 presents the main conclusions.

2. Modelling the best trading strategy

In this paper, a new approach for trading electricity in the Iberian Electricity Market (MIBEL) is presented. In this approach, the decision of traders (buyers and sellers) to buy or sell electricity in the spot or futures markets is guided by a rationale based on the mid-term spot forecast and a premium risk analysis, and therefore is not based solely on past assumptions about the risk propensity of the spot market or the risk aversion of participants who choose the futures market. This last market refers to contracts with physical delivery established in a clearing house, without a direct negotiation between the traders.

For each trading day in the futures market (except for weekends and holidays, when it is closed), the proposed model is intended to help decide whether the trader should buy or sell electricity in the futures market, for a given maturity (in this study from 1 to 6 months ahead), or wait and trade in the spot market, i.e., trade electricity on the day before the respective delivery period. The predicted spot market price for the delivery period, which at this moment is not known, will be formed based on conjectures from the price in the futures market. An accurate forecast of the spot price is therefore essential for optimal decision-making.

Below we present the proposed medium-term forecasting model; an explanation of the selected input and output variables of this model; a statistical analysis of the correlation and dependence between these variables; and the trading strategy based on the risk premium analysis. This is followed by a discussion of the results.

2.1. Proposed forecast model

2.1.1. Literature review: forecasting models

The literature on time-series forecasting is very rich, with a broad set of applications and numerous proposed models. These models aim to accurately map the relations between the future values of the forecast variable (output) and historical data of any related impact factors, including the forecast variable itself (input) (Wang et al., 2019). Classic models, with an inherent higher interpretability (Nie et al., 2022), are considered hard computing approaches, like the autoregressive integrated moving average (ARIMA) or exponential smoothing, as a good way to model the inner dependencies in the forecast variable (Pourdaryaei et al., 2021).

Given the specificities of electricity market price time series and the large availability of data, machine learning (ML) methods are nevertheless the preferred class of electricity price forecasting methods (Imani et al., 2021), in particular different types of artificial neural networks, including feedforward and recurrent neural networks [e.g. Elman networks, Jordan networks, long-short term memory neural network (LSTM) and gated recurrent unit (GRU)] and convolutional neural networks (Jiang & Hu, 2018). The LSTM, first proposed by (Hochreiter & Schmidhuber, 1997), revealed the best forecasting accuracy among the tested neural network models, and therefore was selected to perform the mid-term spot price forecasting. The LSTM algorithm has been applied efficiently and extensively in several works that involve both long and short-term forecasting. Several recent works were applied to the electricity field, namely electricity price forecasting (De Simon-Martin et al., 2020; Meng et al., 2022; Varanasi & Tripathi, 2022; Yang et al., 2022) and electricity load forecasting (Bashir et al., 2022; Chi, 2022; Jin et al., 2022; Karijadi & Chou, 2022; Lee & Cho, 2022; Masood et al., 2022; Saeed et al., 2022; Torres et al., 2022). In addition, LSTM's proven forecasting capabilities have gone far beyond these two common electricity problems. For instance, in (Shen et al., 2021), LSTM is compared with other models such as Autoregressive Integrated Moving Average (ARIMA), Multilayer Perceptron (MLP), Extreme Gradient Boosting (XGBoost), among others, revealing its superior accuracy in forecasting foreign trade rates. While, in (Panja et al., 2022), LSTM proved to be highly capable of predicting oil production, with promising results for data that, when using traditional time series models, are not that accurate. Another advantage of these networks was highlighted in (Peng et al., 2022), where it was shown that multiple energy load prediction method using LSTMs can obtain high accuracy results when the available data are relatively few.

2.1.2. *Input data: selection, analysis and processing*

The input variables utilized in the forecast model are only related to MIBEL prices (without any exogenous variable), as applied to the SPEL base (Spanish zone). Future prices concern monthly maturities (from 1 to 6 months ahead). As in (Monteiro et al., 2020), many of these variables are defined as follows:

1) *DM*: Delivery month represents the month when traded electricity must be delivered, with values in the range [1–12].
2) $PM7\_fut_{n,DM}C$: Average monthly futures price for *DM* in the 7 days preceding trading day *n*. This variable can be calculated by Eq. (1).

$$PM7\_fut_{n,DM} = \frac{1}{nd_7}\sum_{p=n-6}^{p=n} PM7\_fut_{p,DM} \tag{1}$$

where $PM7\_fut_{p,DM}$ is the monthly futures price for *DM* on the negotiation day (p) and nd_7 is the number of trading days in the futures market, i.e., excluding days p with no futures market during the 7 days preceding trading day *n*.

3) $P7\_spot$: Average spot price in the 7 days preceding trading day *n*. Calculated by Eq. (2).

$$P7\_spot_n = \frac{1}{24\times 7}\sum_{p=n-6}^{p=n}\sum_{h=1}^{h=24} P7\_spot_{p,h} \tag{2}$$

where $P7\_spot_{p,h}$ is the spot price for each hour (h) of day p.

4) $PM30\_fut$: Average monthly futures price for *DM* in the 30 days preceding trading day *n*. This variable can be calculated by Eq. (3).

$$PM30\_fut_{n,DM} = \frac{1}{nd_{30}}\sum_{p=n-29}^{p=n} PM30\_fut_{p,DM} \tag{3}$$

where $PM30\_fut_{p,DM}$ is the monthly futures price for *DM* on the negotiation day (p) and nd_{30} is the number of trading days in the futures market, i.e., excluding days p with no futures market in the 30 days preceding trading day *n*.

5) $P30\_spot$: Average spot price in the 30 days preceding trading day *n*. Calculated by Eq. (4).

$$P30\_spot_n = \frac{1}{24\times 30}\sum_{p=n-29}^{p=n}\sum_{h=1}^{h=24} P30\_spot_{p,h} \tag{4}$$

where $P30\_spot_{p,h}$ is the spot price for each hour (h) of day p.

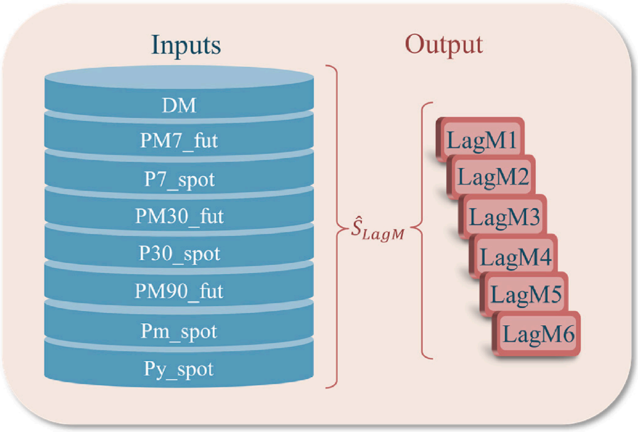


Fig. 1. Inputs and outputs of the forecast model.

6) $PM90\_fut$: Average monthly futures price for *DM* in the 30 days preceding trading day *n*. This variable can be calculated by Eq. (5).

$$PM90\_fut_{n,DM} = \frac{1}{nd_{90}}\sum_{p=n-89}^{p=n} PM90\_fut_{p,DM} \tag{5}$$

where $P90\_fut_{p,DM}$ is the monthly futures price for *DM* on the negotiation day (p) and nd_{90} is the number of trading days in the futures market, i.e., excluding days p with no futures market during the 90 days preceding trading day *n*.

7) Pm_spot: Average monthly spot price before the month of trading day *n*. Calculated by Eq. (6).

$$Pm\_spot_n = \frac{1}{24\times md}\sum_{p=1}^{p=md}\sum_{h=1}^{h=24} Pm\_spot_{p,h} \tag{6}$$

where $Pm\_spot_{p,h}$ is the spot price for each hour (h) of day p and md is the number of days in the month before trading day *n*.

8) Py_spot: Average monthly spot price for the *DM* of the previous year. Calculated by Eq. (7).

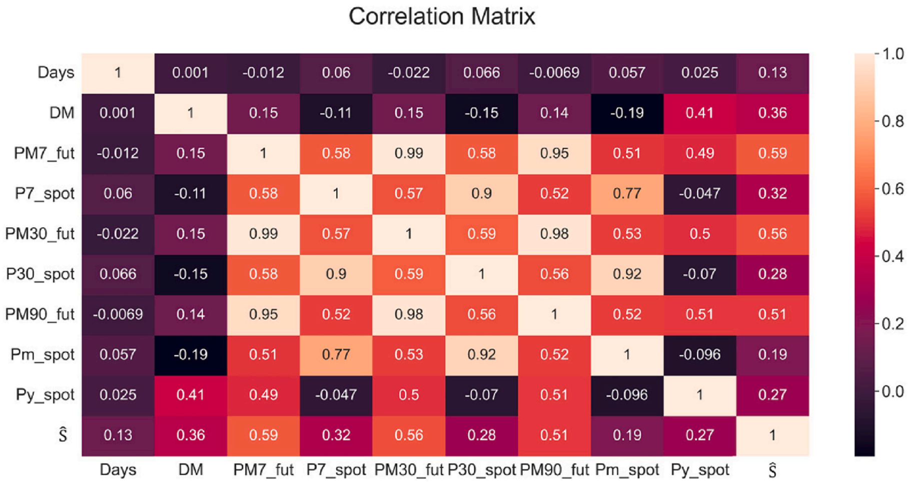
$$Py\_spot_n = \frac{1}{24\times mdy}\sum_{p=1}^{p=mdy}\sum_{h=1}^{h=24} Py\_spot_{p,h} \tag{7}$$

where $Py\_spot_{p,h}$ is the spot price for each hour (h) of day p and mdy is the number of days in the delivery month of the previous year.

The output variable, $\widehat{S}_{LagM}$, is the monthly average spot price forecast on trading day *n* for the delivery months, which can be 1 to 6 months following the month of the trading day and are represented by *LagM*1 to *LagM*6. Fig. 1 illustrates all possible outputs of the forecast model as well as the input variables.

To verify the relationship between the variables, a correlation matrix was computed using the Pearson's coefficient (ρ), Fig. 2. The variable *Days* represents the number of days between trading day *n* and the first day of the delivery month *DM*. Due to a low correlation between all variables, *Days* was removed from the input. As expected, variables related to future prices (*PM*7*_fut*, *PM*30*_fut* and *PM*90*_fut*) were highly correlated among themselves, which was already expected, given that these variables differ only in the horizon of preceding days.

To further test dependency between variables, two statistical tests were performed: the *F-test* to verify linear dependency and *Mutual Information* (MI) to verify nonlinear dependency. Fig. 3 shows the values of these tests for each input variable in relation to the output $\widehat{S}$. The results reveal that the variable *Days* has no dependency on the output, confirming the inference from the correlation matrix and the exclusion of



Correlation Matrix

	Days	DM	PM7_fut	P7_spot	PM30_fut	P30_spot	PM90_fut	Pm_spot	Py_spot	Ŝ
Days	1	0.001	-0.012	0.06	-0.022	0.066	-0.0069	0.057	0.025	0.13
DM	0.001	1	0.15	-0.11	0.15	-0.15	0.14	-0.19	0.41	0.36
PM7_fut	-0.012	0.15	1	0.58	0.99	0.58	0.95	0.51	0.49	0.59
P7_spot	0.06	-0.11	0.58	1	0.57	0.9	0.52	0.77	-0.047	0.32
PM30_fut	-0.022	0.15	0.99	0.57	1	0.59	0.98	0.53	0.5	0.56
P30_spot	0.066	-0.15	0.58	0.9	0.59	1	0.56	0.92	-0.07	0.28
PM90_fut	-0.0069	0.14	0.95	0.52	0.98	0.56	1	0.52	0.51	0.51
Pm_spot	0.057	-0.19	0.51	0.77	0.53	0.92	0.52	1	-0.096	0.19
Py_spot	0.025	0.41	0.49	-0.047	0.5	-0.07	0.51	-0.096	1	0.27
Ŝ	0.13	0.36	0.59	0.32	0.56	0.28	0.51	0.19	0.27	1

Fig. 2. Correlation Matrix between the variables.

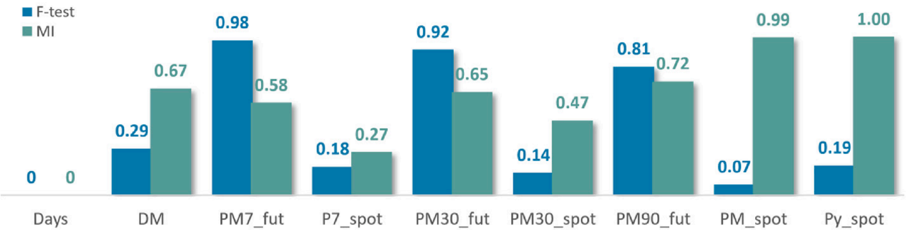


Fig. 3. Statistical dependency test between the input variables in relation to the output.

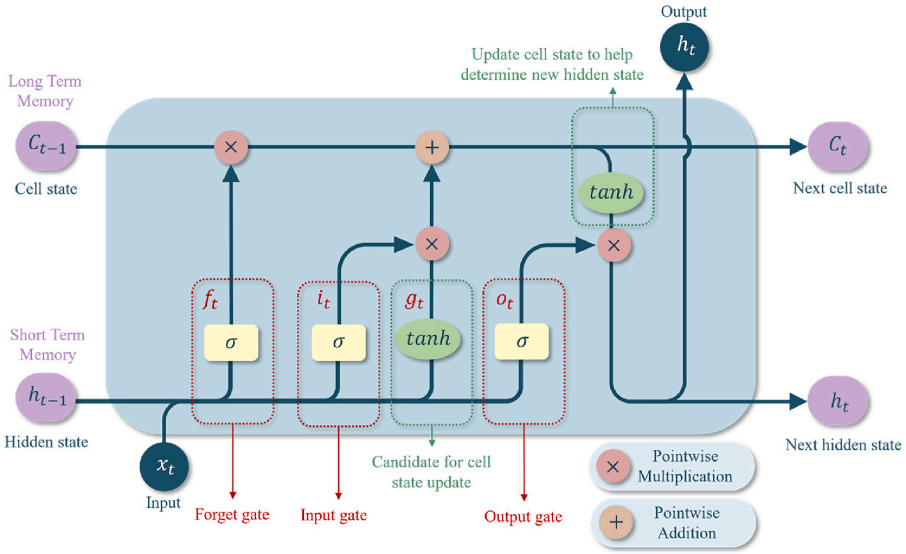


Fig. 4. Representation of LSTM cell.

this variable from the inputs. The variables related to future prices – *PM7_fut*, *PM30_fut* and *PM90_fut* – presented strong linear dependency, while the variables *Pm_spot* and *Py_spot* presented strong nonlinear dependency. These results support the choice of these eight variables as the selected inputs in the forecasting model.

2.1.3. Forecasting model: Long Short-Term memory (LSTM)

An LSTM was implemented to predict the monthly average spot price for the delivery month of the future trade. LSTM networks are a particular kind of Recurrent Neural Network (RNN). Like other common RNNs, they are capable of handling time-sequence data with long-term dependencies, without facing the vanishing gradient problem (Greff et al., 2017).

Fig. 4 represents the internal functioning, i.e., the flow between elements, of a single LSTM module. Each module or cell has a cell state (referred to as long-term memory) and a hidden state (referred to as short-term memory). The cell state transmits information directly through the entire cell. The hidden state can add or remove state information from the cell, under meticulous control by three different gates: the forgetting gate, the input gate, and the output gate. The first step, through the forgetting gate, decides what information is remembered or forgotten, as determined by a sigmoid layer calculated by Eq. (8).

$$f_t = \sigma\left(w_{fx}x_t + w_{fh}h_{t-1} + b_f\right) \tag{8}$$

where σ is the sigmoid function; $w_{.x}$ and $w_{.h}$ are the weight matrices for the input x_t and the recurrent input h_{t-1}, respectively; $b_.$ is the bias vector and t is a time step.

The next step determines what additional information is placed in the cell state. First, the input gate decides which values are updated, as calculated by Eq. (9). Next, a *tanh* layer transforms these values into an activation cost, which can be included in the cell state, Eq. (10). Then, i_t and g_t are combined to update the cell state, as calculated by Eq. (11).

$$i_t = \sigma(w_{ix}x_t + w_{ih}h_{t-1} + b_i) \tag{9}$$

$$g_t = tanh\left(w_{gx}x_t + w_{gh}h_{t-1} + b_g\right) \tag{10}$$

$$C_t = C_{t-1} \odot f_t + g_t \odot i_t \tag{11}$$

where C_{t-1} is a memory cell state and the operation $\odot$ denotes element-wise multiplication of vectors.

Finally, the output gate determines the output from the cell state, by Eq. (12). Then, the current cell state (C_t) is put through the *tanh* layer to determine the new hidden state, i.e., to scale the values between −1 and 1, and multiplied by the output gate's result producing the output (h_t), Eq. (13).

$$o_t = \sigma(w_{ox}x_t + w_{oh}h_{t-1} + b_o) \tag{12}$$

$$h_t = tanh(C_t) \odot o_t \tag{13}$$

After a refining process, the forecasting model consists of two LSTM layers, each with 90 neurons. Both are followed by a dropout layer configured to turn off 20% of the neurons passing information. This reduces the chances of overfitting and increases the generalization capability of the network. Finally, there is a fully connected layer with a sigmoid activation function for the output node.

2.2. Trading strategy

When negotiating, a trader's main objective is making the best choice between buying or selling electricity through a futures contract, with a settled price to be exercised on the delivery period or waiting for the spot market and trading at the one day-ahead electricity price for all days of the delivery month.

At the time of negotiation (day n) the trader must analyse whether the forecasted monthly average spot price ($\widehat{S}$) is higher or lower than the futures price (*MF*) for the delivery month (*DM*), thus determining which is the more favourable decision. As such, the trading strategy is defined for buyers and for sellers by using Eqs. (14) and (15), respectively.

$$\textbf{\textit{Best decision for buyers}} = \begin{cases} buy\ on\ spot\ market, \widehat{S}_{n,DM} < MF_{n,DM} \\ buy\ on\ futures\ market, \widehat{S}_{n,DM} \geq MF_{n,DM} \end{cases} \tag{14}$$

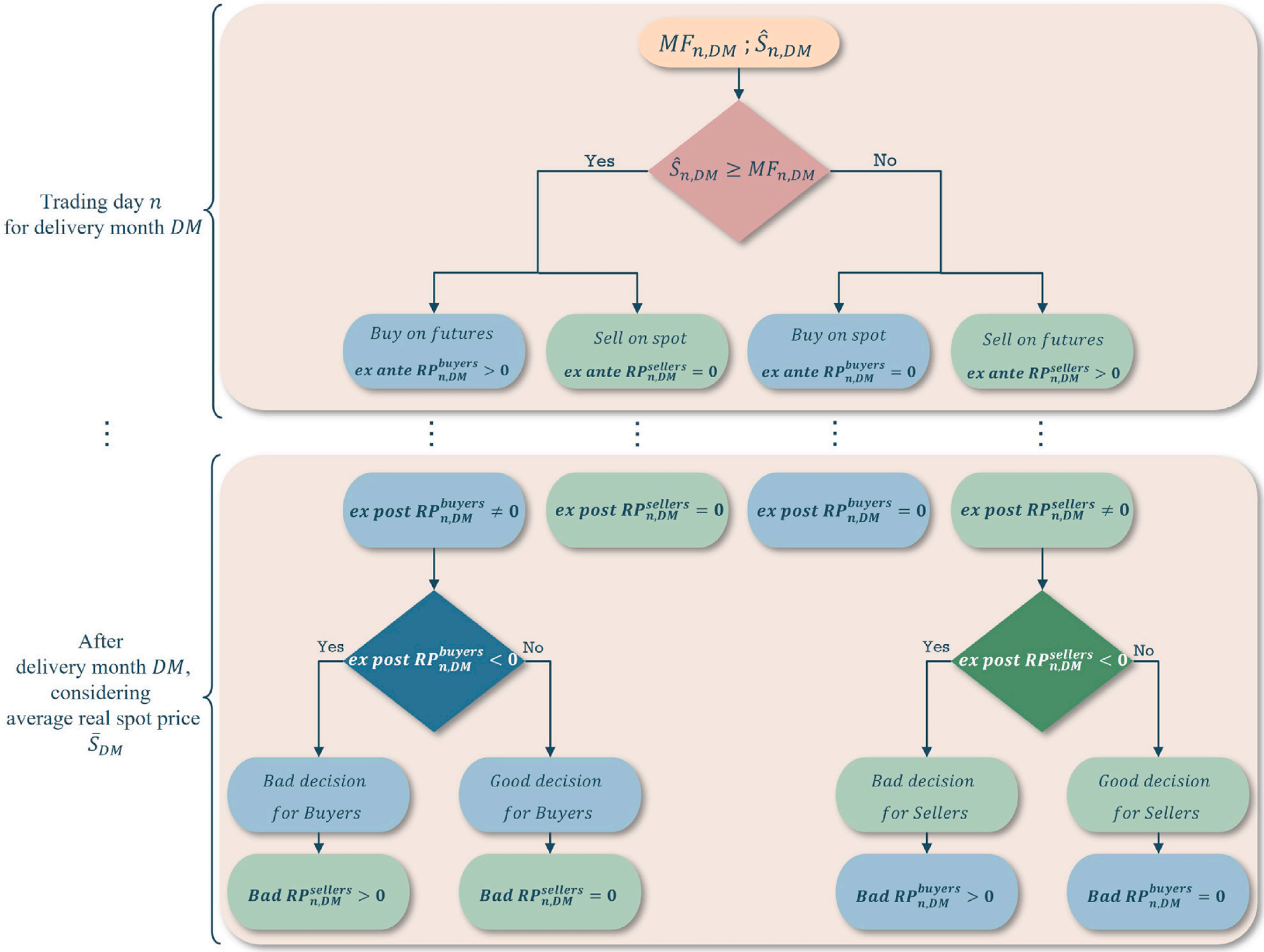


Fig. 5. Flowchart of the stages involving the proposed trading strategy applied to the buyers and sellers.

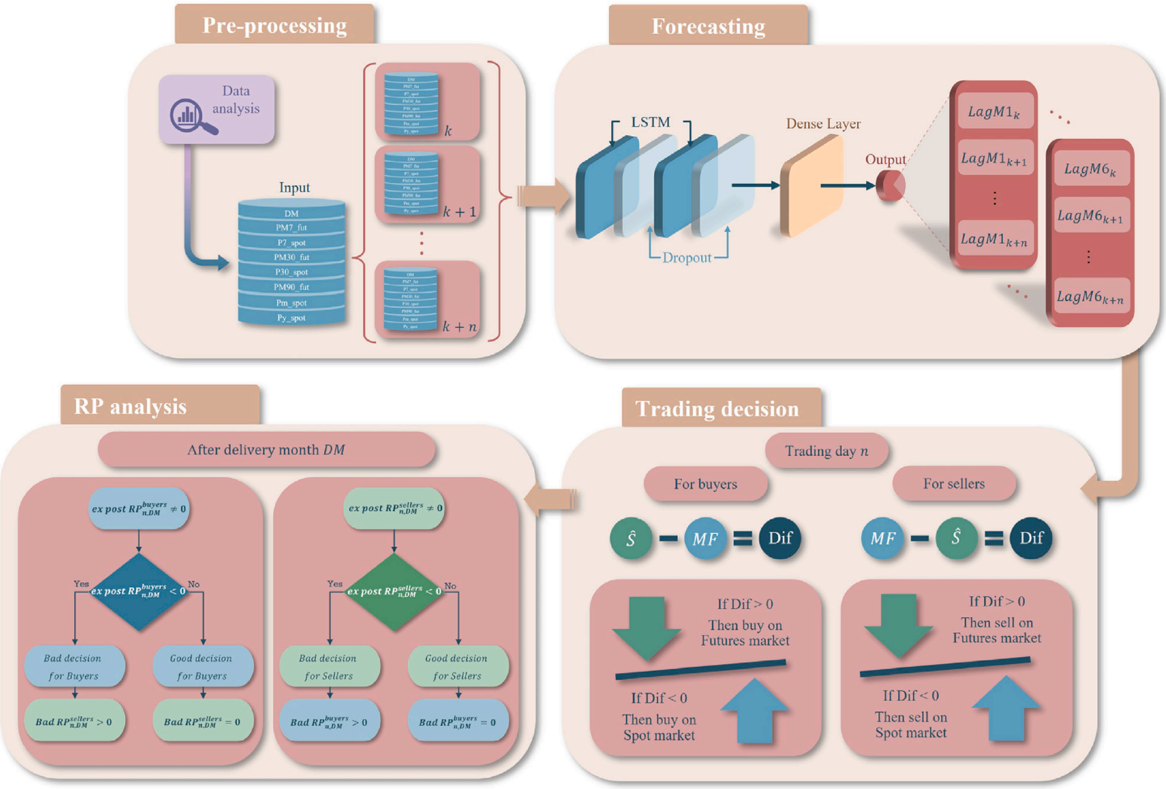


Fig. 6. Overview of the entailed stages that led to the proposed trading strategy.

$$\textbf{\textit{Best decision for sellers}} = \begin{cases} \textit{sell on spot market}, \widehat{S}_{n,DM} \geq MF_{n,DM} \\ \textit{sell on futures market}, \widehat{S}_{n,DM} < MF_{n,DM} \end{cases} \tag{15}$$

The risk premium (*RP*) is the financial term for the difference between the return on any given investment and the return on another investment, considered risk-free. In this work, *RP* denotes the difference between the log of the futures settlement price and the log of the spot average price. The traditional *ex ante* and *ex post* definitions for *RP* were calculated using the logarithmic function, as the authors in (Ferreira et al., 2018; Monteiro et al., 2020), where the *exanteRP* considers the expected (predicted) price $\left(\widehat{S}_{n,DM}\right)$, i.e., the risk is determined with limited knowledge, and the *expostRP* considers the average realized (real) spot price ($\overline{S}_{DM}$), i.e., the risk is determined after the facts, for the respective delivery month. However, other definitions of the *RP* without the logarithmic function are also used in (Bunn & Chen, 2013; Cartea & Villaplana, 2012; Fleten et al., 2015; Furió & Meneu, 2010).

The *exanteRP* is calculated as shown in Eqs. (16) and (17), for buyers and sellers, respectively. The *exanteRP* will always be greater than or equal to zero, where positive values indicate choosing the futures market, while a value of zero means waiting for the spot market is the preferred choice.

$$\textbf{\textit{exante RP}}^{buyers}_{n,DM} = \begin{cases} 0, \widehat{S}_{n,DM} < MF_{n,DM} \\ ln\left(\widehat{S}_{n,DM}\right) - ln\left(MF_{n,DM}\right), \widehat{S}_{n,DM} \geq MF_{n,DM} \end{cases} \tag{16}$$

$$\textbf{\textit{exante RP}}^{sellers}_{n,DM} = \begin{cases} 0, \widehat{S}_{n,DM} \geq MF_{n,DM} \\ ln\left(MF_{n,DM}\right) - ln\left(\widehat{S}_{n,DM}\right), \widehat{S}_{n,DM} < MF_{n,DM} \end{cases} \tag{17}$$

The assumptions of the *exanteRP* are evaluated by determining the *expostRP* for buyers and sellers, based on the monthly average realized spot price, for the delivery month, as given by Eqs. (18) and (19), respectively.

$$\textbf{\textit{expost RP}}^{buyers}_{n,DM} = \begin{cases} 0, \widehat{S}_{n,DM} < MF_{n,DM} \\ ln\left(\overline{S}_{DM}\right) - ln\left(MF_{n,DM}\right), \widehat{S}_{n,DM} \geq MF_{n,DM} \end{cases} \tag{18}$$

$$\textbf{\textit{expost RP}}^{sellers}_{n,DM} = \begin{cases} 0, \widehat{S}_{n,DM} \geq MF_{n,DM} \\ ln\left(MF_{n,DM}\right) - ln\left(\overline{S}_{DM}\right), \widehat{S}_{n,DM} < MF_{n,DM} \end{cases} \tag{19}$$

Accordingly, to Eqs. (18) and (19), when *expostRP* is non-zero, it can assume positive or negative values. Positive values represent profits or savings, while negative values represent bad decisions (when it would have been better to wait for the spot market), i.e., $\overline{S}_{DM} < MF_{n,DM}$ when $\widehat{S}_{n,DM} \geq MF_{n,DM}$ for buyers and $\overline{S}_{DM} > MF_{n,DM}$ when $\widehat{S}_{n,DM} \leq MF_{n,DM}$ for sellers.

In the setup, however, when *ex ante RP* is zero, the decision to wait for the spot market is not always the best trading strategy. Consider the case when $ex\,ante\ RP^{buyers}_{n,DM} > 0$ (implying the decision to buy in the futures market), but $ex\,post\ RP^{buyers}_{n,DM} < 0$ (implying a bad decision, that it would have been more favourable for the buyer to wait for the spot market). Conversely, for the seller in this case $ex\,ante\ RP^{sellers}_{n,DM} = 0$ and $x\,post\ RP^{sellers}_{n,DM} = 0$, implying the seller should wait for the spot market (also a bad decision), when in fact the seller's profit would have been higher in the futures market.

Therefore, this paper proposes a slightly different interpretation of the *RP*, which includes a new variable called "*BadRP*", for when a bad decision occurs. This variable will have positive values for buyers if sellers have losses when trading in the futures market, i.e., when $\left(\widehat{S}_{n,DM} < MF_{n,DM}\right)$ and $\left(expostRP^{sellers}_{n,DM} < 0\right)$; and will be zero if sellers have profits. On the other hand, it will be positive for sellers if buyers make a bad decision, i.e., when $\left(\widehat{S}_{n,DM} \geq MF_{n,DM}\right)$ and $\left(expostRP^{buyers}_{n,DM} < 0\right)$; and it will be zero if they make a good decision. *BadRP* can be calculated by using Eq. (20) for buyers and Eq. (21) for sellers.

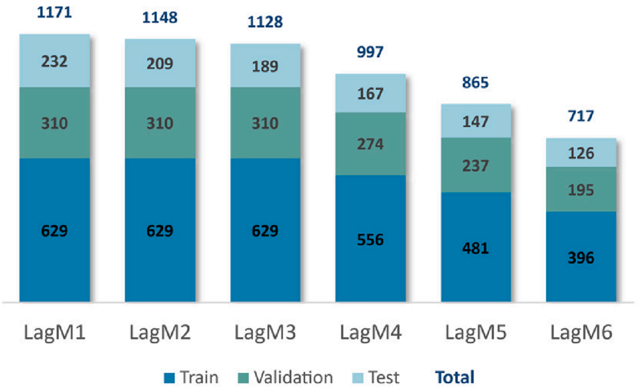


Fig. 7. Splitting the dataset into training, validation and testing for each forecast model (*LagM*1 to *LagM*6).

$$BadRP^{buyers}_{n,DM} = \begin{cases} 0, expostRP^{sellers}_{n,DM} \geq 0 \\ ln(\overline{S}_{DM}) - ln(MF_{n,DM}), (\widehat{S}_{n,DM} < MF_{n,DM}) and \left(expostRP^{sellers}_{n,DM} < 0\right) \end{cases} \tag{20}$$

$$BadRP^{sellers}_{n,DM} = \begin{cases} 0, expostRP^{buyers}_{n,DM} \geq 0 \\ ln(MF_{n,DM}) - ln(\overline{S}_{DM}), (\widehat{S}_{n,DM} \geq MF_{n,DM}) and (expostRP^{buyers}_{n,DM} < 0) \end{cases} \tag{21}$$

Fig. 5 presents the flowchart of the decisions of buyers and sellers. First, in the trading day *n* with information only of the forecasted monthly average spot price ($\widehat{S}_{n,DM}$) and futures price (*MF*) for the delivery month (*DM*), then we determine the risk premium (*exanteRP*) to get a first assessment of the possible risk associated with the trading decision. After the delivery month of the future contract, it is then possible to analyze these decisions considering the real monthly average spot price ($\overline{S}_{DM}$), so we calculate the risk premium (*expostRP*) and (*BadRP*) and check if good decisions were made, i.e., evaluate the quality of the trading decisions.

So, to recapitulate the steps described in the previous sections, first, a statistical analysis is performed to verify the correlation between the input and output variables for the forecast model. Next, the LSTM recurrent neural network model is implemented to forecast the monthly average spot price for the futures delivery months (1 to 6 months after the settlement), represented by *LagM*1 to *LagM*6. Finally, a predictive trading strategy using premium risk analysis supports the trader (buyer or seller) decide between trading in the futures market or the spot market. This whole process is schematically represented in Fig. 6.

3. Results and discussions

3.1. Data analysis

Historical energy price data from the Iberian electricity market (MIBEL) were used to test the forecasting model, as well as the proposed trading strategy. The data comprised the period from January 2015 to August 2019. These data include monthly futures prices for base-load in the Spanish zone (referred to as SPEL base monthly futures) and the prices in the daily spot market over the same period.

For the forecasting model, the data were divided, for each *LagM* (1 to 6), into training, validation, and test data (see Fig. 7). Each forecast model was trained using 33% of the training data for validation, selected from the last samples before shuffling. To avoid overfitting, training was performed using early stopping as the stopping criterion. The widely used Adam optimizer was chosen as the training algorithm for the LSTM network, using the mean squared error as the loss metric. Each forecast model included two LSTM layers with 90 neurons, each followed by a dropout layer with 20% ratio to increase the network generalization capability, and lastly a dense layer with one output neuron and sigmoid

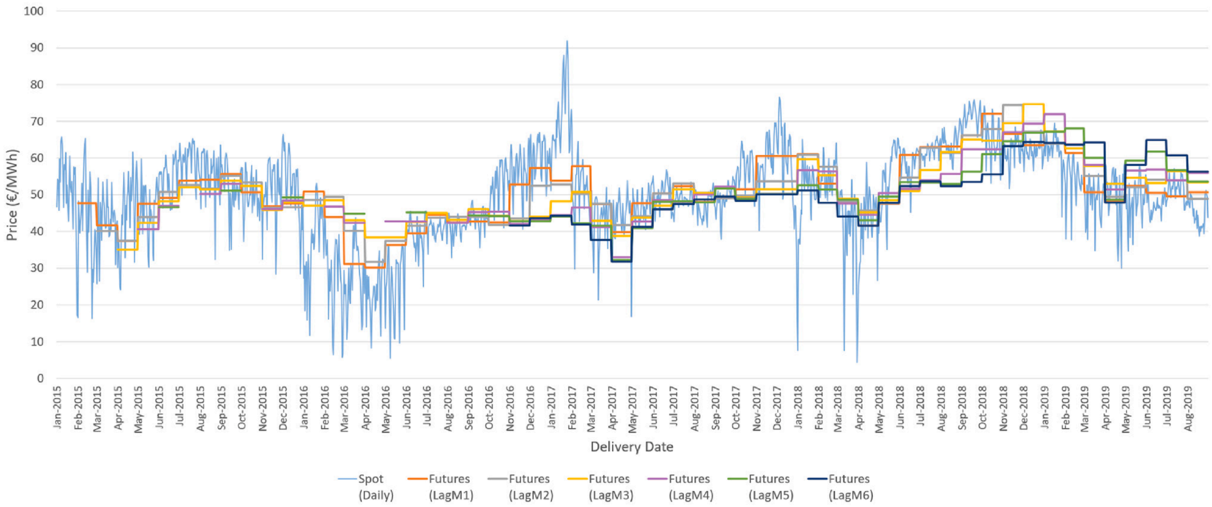
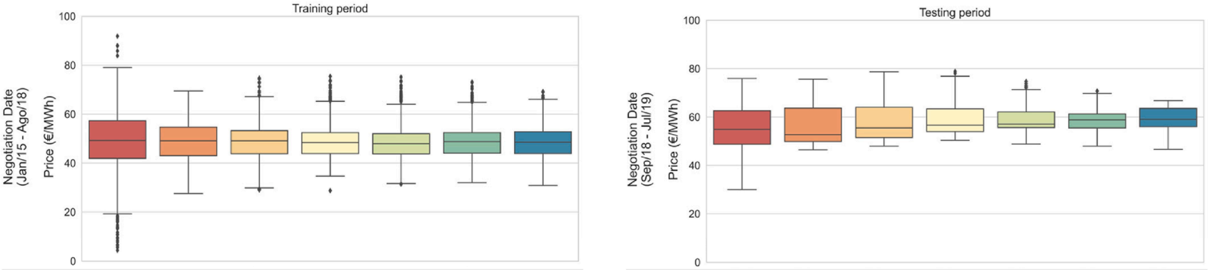


Fig. 8. Spot (daily) and futures (monthly average) price for MIBEL in the delivery date (January 2018 to August 2019).



Statistic	Spot (Daily)	Futures (LagM1)	Futures (LagM2)	Futures (LagM3)	Futures (LagM4)	Futures (LagM5)	Futures (LagM6)
Delivery Date	Jan/15-Aug/18	Feb/15-Sep/18	Mar/15-Oct/18	Apr/15-Nov/18	May/15-Dec/18	Jun/15-Jan/19	Nov/16-Feb/19
Mean	50.81	49.39	49.46	49.12	49.07	49.37	49.24
Minimum	15.88	27.50	29.00	28.75	31.38	32.02	30.87
Maximum	91.88	69.50	74.70	75.38	75.18	73.15	69.25
SD	11.28	8.44	7.83	7.35	7.48	7.55	7.98
Skewness	-0.30	-0.09	0.38	0.78	0.88	0.69	0.35
Kurtosis	0.50	-0.23	0.23	0.76	1.04	0.80	0.03
Samples	939	939	939	939	830	718	591

Statistic	Spot (Daily)	Futures (LagM1)	Futures (LagM2)	Futures (LagM3)	Futures (LagM4)	Futures (LagM5)	Futures (LagM6)
Delivery Date	Sep/18-Aug/19	Oct/18-Aug/19	Nov/18-Aug/19	Dec/18-Aug/19	Jan/19-Aug/19	Feb/19-Aug/19	Mar/19-Aug/19
Mean	57.88	57.23	58.33	59.24	58.64	58.22	58.41
Minimum	30.02	46.38	47.95	50.35	48.79	47.96	46.67
Maximum	75.89	75.63	78.70	78.79	74.73	70.75	66.76
SD	8.73	8.14	8.21	7.28	6.15	5.87	5.90
Skewness	-0.02	0.46	0.63	1.00	0.99	-0.02	-0.67
Kurtosis	-0.41	-1.18	-0.68	0.02	0.42	-0.50	-0.58
Samples	232	232	209	189	167	147	126

Fig. 9. Descriptive statistics of prices for training and testing period.

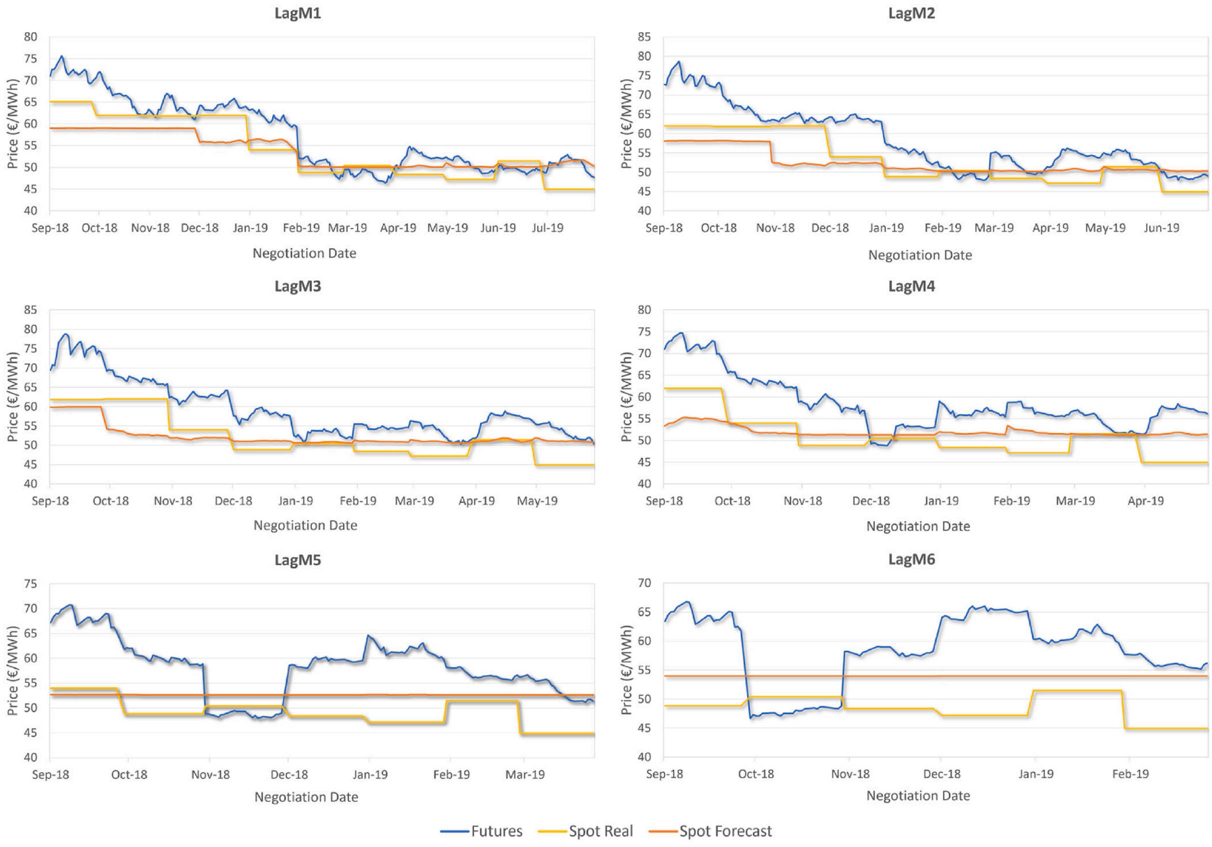


Fig. 10. Predictions of the Spot Forecast, Spot Real and Futures prices in the testing period for each maturity (*LagM*).

activation function. This specific configuration was chosen among several tested configurations because it produced the best results across the different forecasting horizons. The test dataset comprised the months of September 2018 to August 2019. Inspection of this time series indicates this was a difficult period, given the exceptionally high spot and futures prices in September 2018 compared to the training dataset values.

Fig. 8 shows the daily average spot price and the monthly average futures price for *LagM*1 to *LagM*6. Obviously, the first months of the training period do not have values for all time horizons. In addition, some months with negotiating dates had no contracts signed for *LagM*4, *LagM*5 and *LagM*6. For example, for *LagM*6, the first contract was signed in May 2016, with a delivery date in November 2016.

In turn, Fig. 9 presents the descriptive statistics for the spot (daily) and futures prices for the training and testing periods, respectively. The negotiation dates from January 2015 to August 2018 were used for training, while the period between September 2018 to July 2019 was considered for testing. The spot price values (daily average) correspond to the values in these same periods, considering that this market operates every single day, contrary to the futures market. The futures prices correspond to the specific period of the delivery date of each *LagM*, described in Fig. 9. The minimum and mean values for the prices were higher for the test period. The standard deviation (SD) for the spot price was lower in the testing period. The maximum value of the spot price

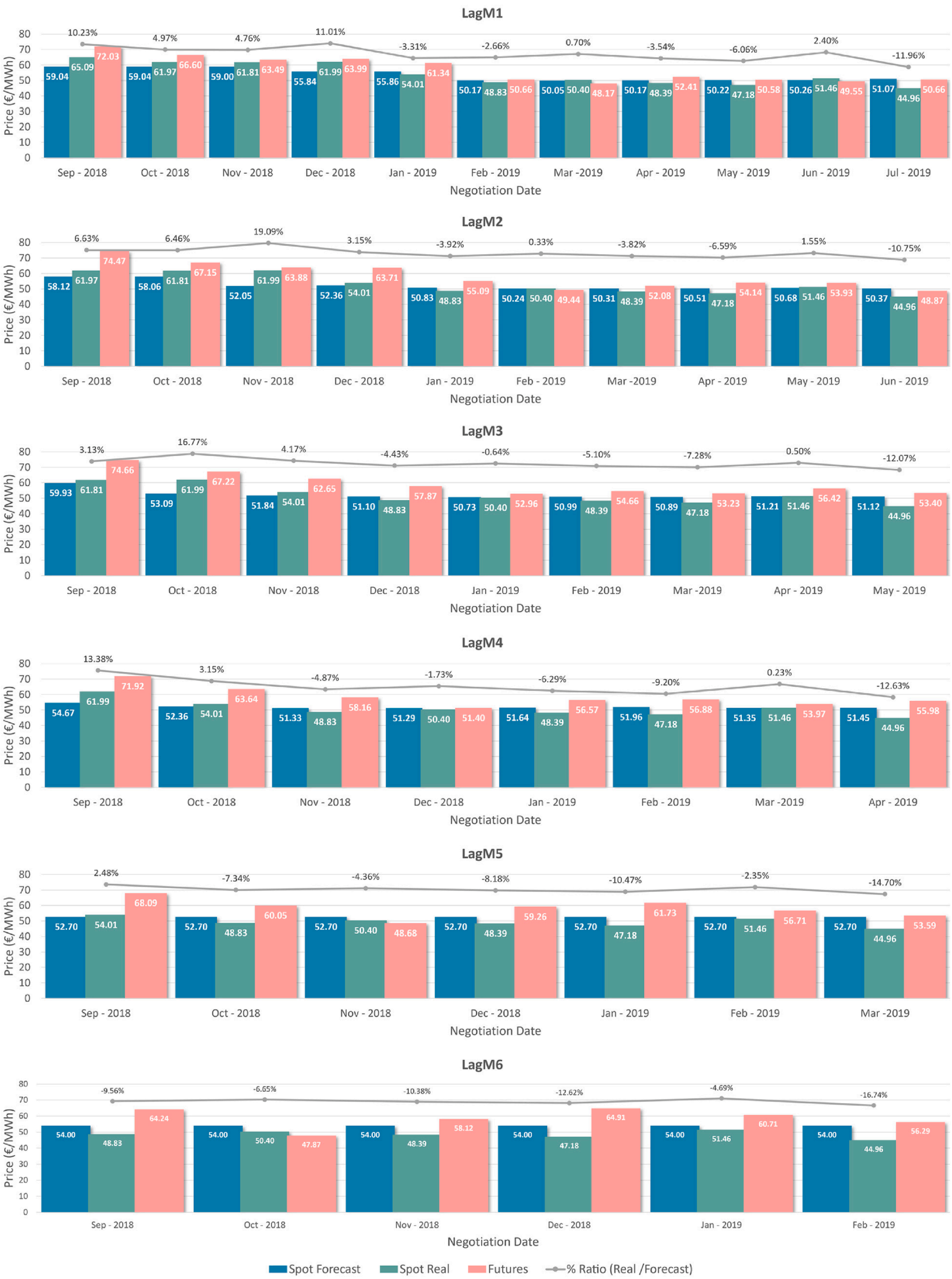
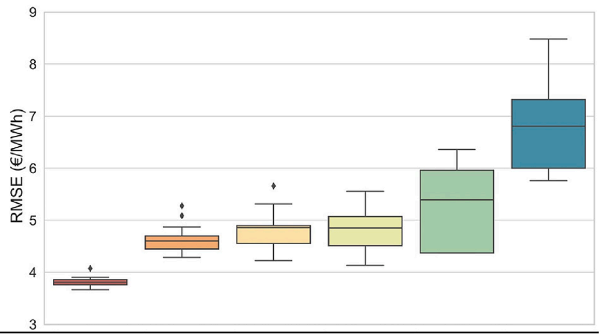


Fig. 11. Monthly average of the Futures, the Spot Forecast and the Spot Real prices in the testing period for each maturity (*lagM*).

was higher in the training period. For the futures prices of both periods, the SD was slightly lower for longer maturities (large *LagM*), indicating greater variability for shorter maturities.

3.2. *Forecast results*

Forecasts were performed for each day of the test period, providing six daily forecasts for the six *LagM*, with forecasting horizons of 1 to 6



Statistic	LagM1	LagM2	LagM3	LagM4	LagM5	LagM6
Mean	3.81	4.62	4.82	4.77	5.36	6.78
Minimum	3.66	4.28	4.22	4.13	4.37	5.76
Maximum	4.07	5.28	5.66	5.55	6.36	8.48
SD	0.09	0.24	0.33	0.39	0.76	0.82
Skewness	0.95	1.23	0.54	-0.04	-0.21	0.40
Kurtosis	2.76	1.91	1.32	-0.66	-1.48	-0.62

Fig. 12. Root mean squared error (RMSE) of the Spot Forecast in relation to the Spot Real.

Table 1
Main parameters setting for the comparison models.

Methods	Main parameters
Persistence	The forecast value was defined as the average monthly spot price of the delivery month of the previous year.
ANN	The first hidden layer size is set to 64 and the second hidden layer size is set to 32, the activation function is set to use Rectified Linear Unit, the last layer of size one is set to sigmoid activation function and the solver is set to use Adam. A threshold of 33% of training dada to validation. As the LSTM model, the ANN was trained 20 times and the results showed are de mean of all evaluations.
ARIMA	For this model was used $p = 1$, $d = 1$ and $q = 1$, where p is autoregressive (AR) term order, d is order of non-seasonal difference and q is order of the moving average (MA) term. These parameters were set based on the autocorrelation function (ACF), the partial autocorrelation function (PACF) and the Augmented Dickey-Fuller (ADF) test to verify the series stationarity.
ARMA	For this model was used $p = 1$ and $q = 1$. Based on the Augmented Dickey-Fuller (ADF) test was used ARIMA without non-seasonal difference ($d = 0$).
XGBoost	Number of estimators = 100, max depth = 3, subsample = 0.7, and colsample bytree = 0.7.
RF	Number of estimators = 300, min samples leaf = 3 and max features = 8.

months. The plot in Fig. 10 illustrates the actual monthly average spot price in the delivery month (*DM*), $(\overline{S}_{DM})$, labeled as “Spot Real”; the forecast of the monthly average spot price, $(\widehat{S}_{n,DM})$, labeled as “Spot Forecast”; and the monthly futures settlement price for trading day *n*, $(MF_{n,DM})$, labeled as “Futures”, for each *LagM*.

The monthly average of the Futures price, *MF*, the Spot Forecast price, $\widehat{S}$, and the Spot Real price, $\overline{S}$, and also the percentage of the ratio between the Spot Real and the Spot Forecast, for each *LagM*, are shown in Fig. 11. The figure reveals that the monthly average Futures prices remained higher than the average spot prices, except for March and June for *LagM*1, February for *LagM*2, November for *LagM*5, and October for *LagM*6. Most often, the Spot Forecast was higher than the Spot Real, although, importantly, the forecast error was not significantly high.

The forecast error was calculated using the mean squared error (RMSE) according to Eq. (22).

$$RMSE_{LagM} = \sqrt{\frac{\sum_{DM=DM_i}^{DM=DM_f}\sum_{n=ni_{LagM,DM}}^{n=nf_{LagM,DM}}\left(\widehat{S}_{n,DM} - \overline{S}_{DM}\right)^2}{\sum_{DM=DM_i}^{DM=DM_f} ND_{LagM,DM}}} \tag{22}$$

where $RMSE_{LagM}$ corresponds to the root mean squared error of the Spot Forecast $(\widehat{S}_{n,DM})$ for each *LagM* (1 to 6); $\overline{S}_{DM}$ is the average of Spot Real for the delivery month (*DM*); DM_i is the initial delivery month and DM_f is the final delivery month in the testing period; $ni_{LagM,DM}$ is the first negotiation day; $nf_{LagM,DM}$ is the last negotiation day for the delivery month *DM*, with a maturity *LagM*; and $ND_{LagM,DM}$ is the total number of negotiation days for delivery month *DM* with a maturity *LagM*. Notice that only negotiation days *n* are included in the sum.

Each forecast model, i.e., the model for each *LagM*, was trained and tested 20 times. Fig. 12 shows the RMSE results of the 20 trained models from each *LagM*. As expected, results for larger horizons presented higher RMSE and standard deviation (SD). The best forecasting model achieved an RMSE equal to 3.66 for *LagM*1 and an RMSE of 5.76 for *LagM*6. The model with the lowest RMSE value was chosen as the best model to make predictions, but in general, all models for all *LagM* showed good prediction results.

3.3. Model comparison

As a benchmark, five other well-known methods were used to predict the monthly average spot price $(\widehat{S}_{n,DM})$, between them, persistence method (Ghayekhloo et al., 2019), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) (Mishra et al., 2023), Artificial Neural Networks (ANN) (Nascimento et al., 2019), Extreme Gradient Boosting (XGBoost) (Bitirgen & Filik, 2020) and Random Forest (RF) (Kara et al., 2021).

Below, Table 1 presents the main parameters settings for comparison models and some main aspects in relation the implementation of models. All of these models were tested using the same available training and testing data of the LSTM model.

The forecast results obtained by the LSTM model proposed in this paper were compared with the results obtained by these comparison models, as shown in Table 2. The RMSE values, clearly show the benefits of the proposed forecasting model, where for the testing dataset, the LSTM model was able to outperform all the baseline models for all the Lags. The worst performance was given by the ARIMA model for *LagM* = 1 with an RMSE of 18.46 **€/MWh**, an increase of almost 5 times in relation to the RMSE of 3.81 **€/MWh** achieved by the proposed LSTM model. With the best mean RMSE value of 5.03 **€/MWh,** the LSTM performance was then followed by the ARMA and ANN model, with mean RMSE of 6.35 **€/MWh** and 6.95 **€/MWh**, respectively. Moreover, apart from the ARIMA and the RF model (in the last Lag), as expected, as the forecasting horizon increases, there is an obvious degradation of the forecasting accuracy, but again the proposed LSTM is able to present a very reliable error accuracy, that does not go beyond the 7 **€/MWh.**

Additionally, the forecast results obtained by the LSTM model with a tailored input data selection were also compared with the results obtained in (Monteiro et al., 2020), where the authors employed an ELM neural network model and an ordinary least square forecasting model (OLS), as a predictive trading strategy applied to the MIBEL market, i.e., the same test scenario of this work. Although the OLS model achieved the best RMSE results for *LagM*5 and *LagM*6, the prediction results obtained by the LSTM model was better than the mean value of 5.82 €/MWh. Furthermore, the results achieved by LSTM were better than ELM for all lags. Again, The RMSE values, for each *LagM* and for all the

Table 2
Root mean square error (RMSE) values for the testing period for all models compared.

RMSE									
LagM(Months)	LSTM (€/MWh)	ELM (€/MWh)	OLS (€/MWh)	Persistence (€/MWh)	ANN (€/MWh)	ARIMA (€/MWh)	ARMA (€/MWh)	XGBoost (€/MWh)	RF (€/MWh)
1	**3.81**	4.71	7.20	9.71	5.76	18.46	6.31	6.32	7.70
2	**4.62**	5.60	6.86	9.75	7.33	13.41	5.01	6.13	7.42
3	**4.82**	6.19	5.94	10.37	6.50	11.38	5.12	6.47	7.40
4	**4.77**	6.61	5.30	10.65	6.49	11.92	5.55	7.46	11.40
5	5.36	7.03	**4.84**	10.66	7.01	13.00	7.79	8.52	12.06
6	6.78	8.24	**4.75**	11.31	8.63	12.82	8.32	9.31	8.42
Mean	**5.03**	6.40	5.82	10.41	6.95	13.50	6.35	7.37	9.07
Error Improvement		21%	14%	52%	28%	63%	21%	32%	45%

The best results are highlighted in **bold**.

compared models, are shown in Table 2, where it is highlighted in the last row, the error improvement (reduction) in the mean RMSE value, achieved by the proposed LSTM model in comparison with every other benchmark model.

3.4. Risk premium analysis

The forecasted spot price values allow a trader (buyer or seller) to calculate the cost/profit when following the suggestion of the Risk Premium (*RP*), as seen in the previous section. If the Spot Forecast price-series is lower than the Futures price, then the decision should be buying in the spot market and selling in the futures market. Fig. 13 shows the results of the RP proposed in this paper, for each *LagM*, of both buyers and sellers, where the *exanteRP* is denoted by the blue dotted line. A risk of zero means one should wait for the spot market, whereas positive risk values suggest trading in the futures market. The *expostRP* is represented by the green dotted line, where zero means trading in the spot market; positive values represents trading in the futures market; and negative values imply the *exanteRP* decision was trading in the futures market, but waiting for the spot market would have been a better decision (trading in the futures market was a bad decision). Finally, the *BadRP* is represented by red columns, indicating that waiting for the spot market was a bad decision and trading in the futures market would have been better. When the green line is greater than the blue line, results were better than expected; conversely, if the green line is lower than the blue line, gains were not as good as expected.

Note that when the *expostRP* for buyers is negative (bad decision) the *BadRP* of sellers is positive (also bad decision) and vice versa. For *LagM*4 and *LagM*6, the *expostRP* was never negative for any of the traders (buyers and sellers) and therefore the *BadRP* was always zero, implying all decisions were correct.

Regarding decisions to buy in the spot market or sell in the futures market, only *LagM*1 produced bad decisions (just 2% among 70% of such decisions); the other horizons had no such bad decisions. Regarding decisions to buy in the futures market or sell in the spot market, *LagM*1 and *LagM*2 had the highest percentages of bad decisions (35% of 30% of such decisions for *LagM*1 and 42% of 28% for *LagM*2). This is greatly justified by the actual Spot price being lower than both the Spot Forecast and Futures, in this period. The percentage of these trading decisions is showcased in Fig. 14, and as we saw, with the exception of a minority of decisions for the first two Lags, the residual levels of bad decisions attest the validity of the proposed strategy, for buyers and sellers to approach the different market options based on a reliable single point-medium term forecast.

3.5. Trading decision analysis

The expected average monthly cost for buyers and the expected average monthly profit for sellers were calculated, for the entire test period, based on the monthly average spot price forecasts and their implied decisions regarding futures prices. When the decision was to buy in the futures market, the expected cost and the real cost were calculated from the Futures price; when the decision was to buy in the spot market, the expected cost was calculated based on the Spot Forecast price and the real cost calculated from the Spot real price. Profit calculation was analogous for sellers.

The expected and realized average monthly cost and profit and the percentage of the ratio between the Real and the Expected are highlighted in Fig. 15. For buyers, a positive percentage means that the actual cost was higher than expected, even if no bad decisions were made; conversely, for sellers, a negative percentage means that the actual profit was lower than expected, regardless of whether only good decisions were made.

Regarding the accuracy of the forecast, the more accurate the monthly average spot price forecasts, the closer traders will be to the real cost, when deciding their trading strategy. Thus, allowing a better financial planning, that maximizes the market participant's gains. In financial terms, a positive forecast error and a negative forecast error have a different impact on each trade, given its implication of correctly or incorrectly, buy or sell in one of two very different markets (spot vs futures market). So, in all conditions it is extremely important for the forecast model to be as accurate as possible.

4. Conclusions

This paper presents an electricity trading strategy in the Iberian Electricity Market (MIBEL) to help traders (buyers and sellers) decide between trading in the futures market or the spot market. The trading strategy is based on the mid-term forecast of the monthly average spot price provided by a forecasting model implemented by a Long Short-Term Memory (LSTM) recurrent neural network, where the forecasted value of the Spot price and the Futures settlement price indicate the most favourable trading decision.

To estimate the advantage of trading in the futures market (of varying monthly maturity) or waiting for the spot market, a risk premium (*RP*) was defined using three different approaches: the *exanteRP*, based on predictive spot price; the *expostRP*, based on the real spot price; and the *BadRP* to indicate bad decisions. The *exanteRP* revealed itself as a good trading strategy, with values very close to the *expostRP* (which can only be calculated *a posteriori*, based on the real spot values). Therefore, the forecast model proved to be very efficient, having resulted in a 21% and 14% improvement in the mean RMSE across all the forecasting horizons when compared with the ELM and OLS methods (from the reference work in (Monteiro et al., 2020)). While, against the baseline models, for all the Lags, the LSTM model was able to significantly outperform them, with mean RMSE error improvements ranging from 21% to 63%. Optimal results for longer horizons are more difficult, but the model's results were very satisfactory, confirming the feasibility of predicting average monthly spot prices only slightly different from their real value. The *BadRP* confirmed the promising results of the prediction, since the percentages were low and in some cases were zero for the entire test period.

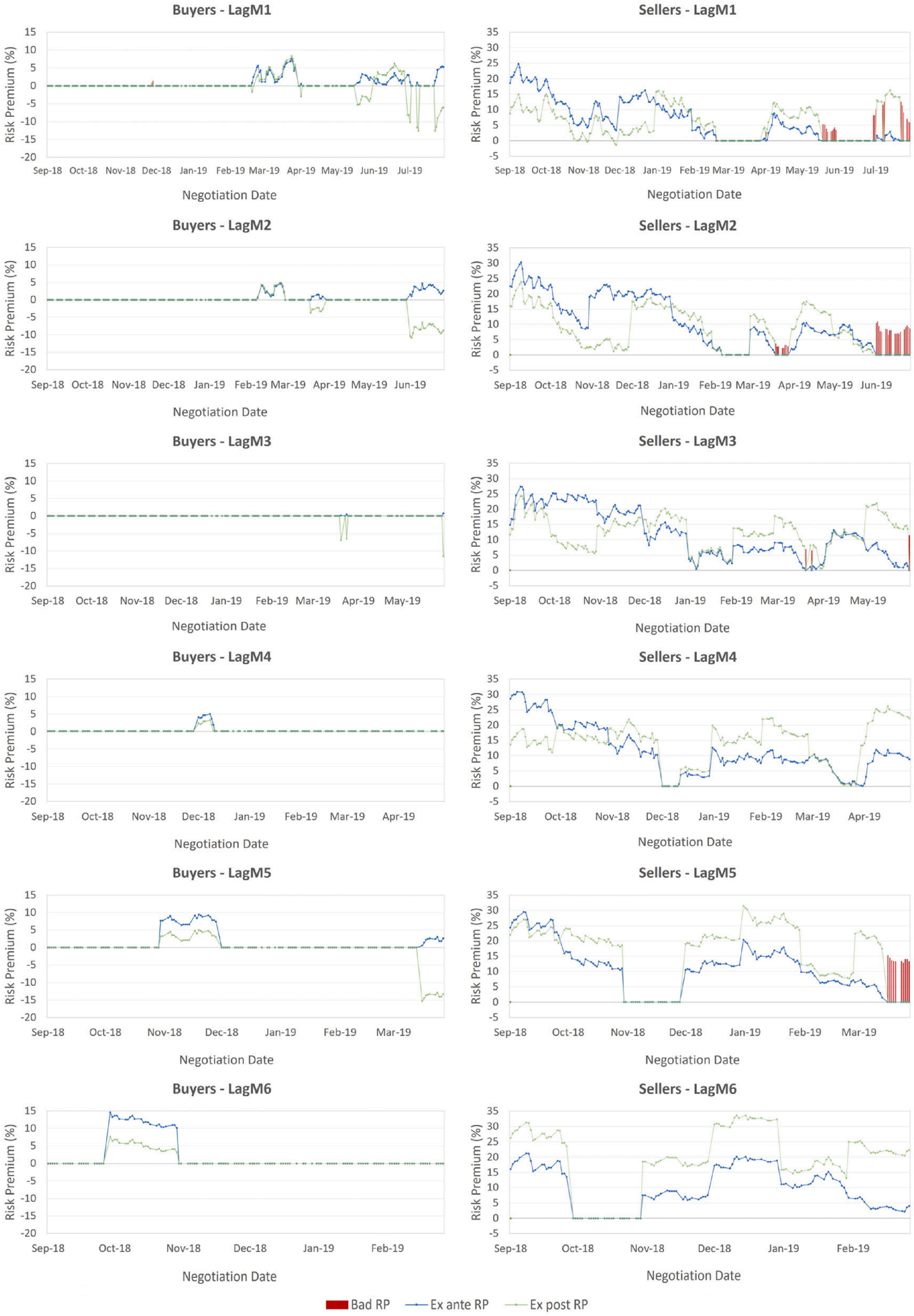


Fig. 13. Risk Premium (*RP*) values for buyers and sellers following the *exanteRP*, *expostRP* and *BadRP* for each *Lag*.

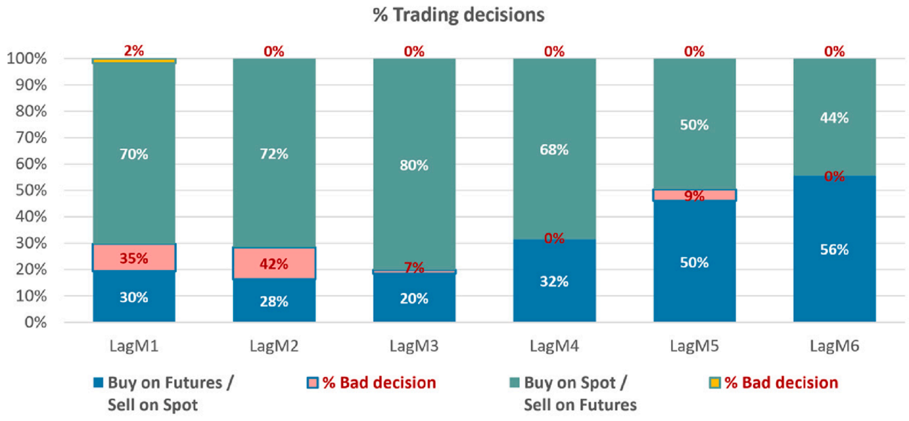


Fig. 14. Percentage of trading decisions.

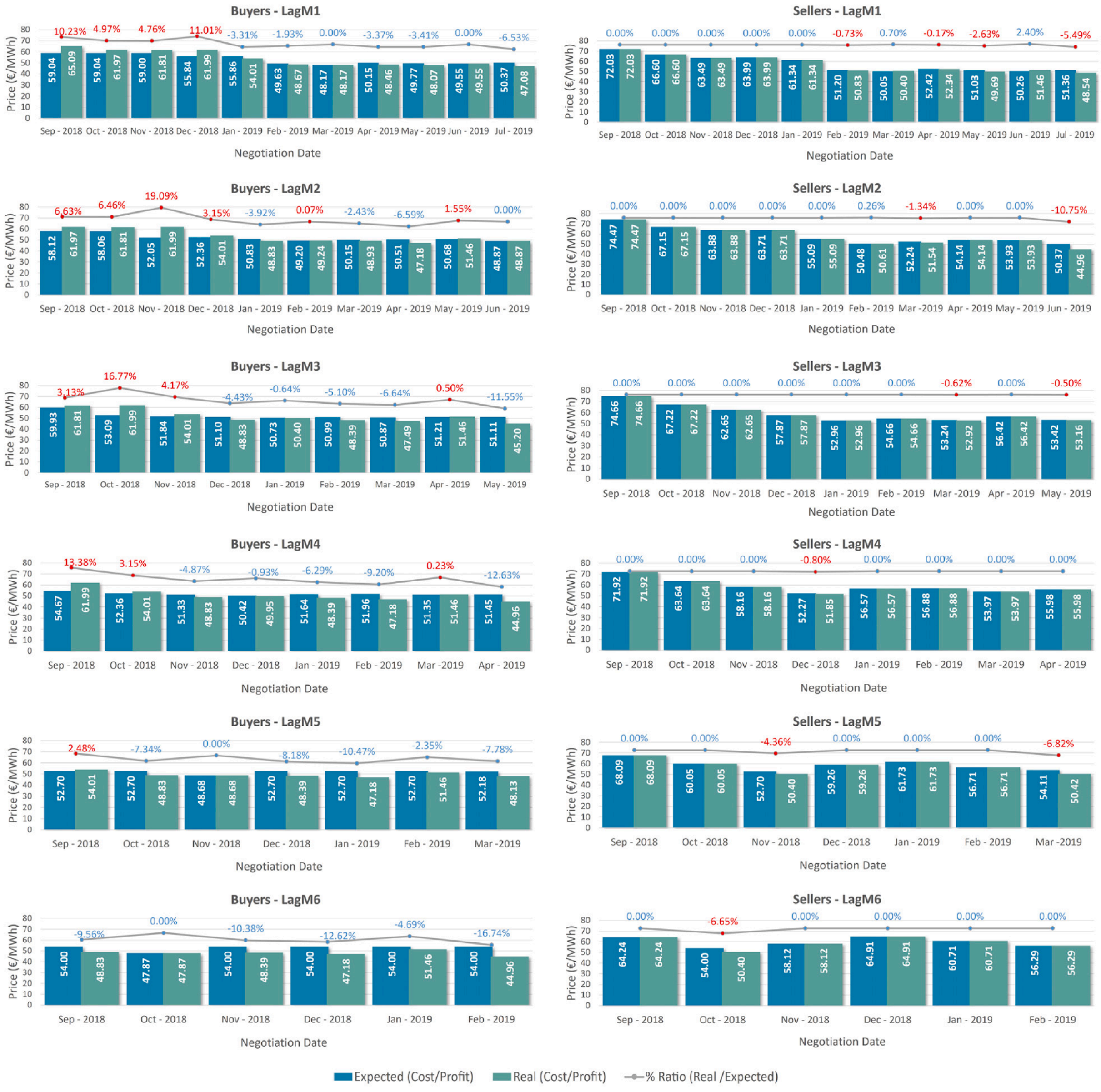


Fig. 15. Cost/Profit expected and real for buyers/sellers.

In addition, for each maturity horizon (*LagM*), an analysis of expected cost and profit was performed based on the forecasted monthly average spot price and the most favourable decisions based on the *exanteRP*. For all *LagMs* (1 to 6 months), this analysis showed that the expected cost/profit was very close to the real values, with an average percentage of real: expected ratio of approximately 0% for the entire test period, for all *LagMs* of both buyers and sellers.

The analyses in this paper constitute a novel approach with excellent results. The strategies were analysed using data from between September 2018 and July 2019 (negotiation dates), a period with atypical high futures prices, which indicated financial loss for the buyers and some gains for the sellers had they traded in the futures market for that entire period. Following the trading strategy proposed in this paper, overall (average of the test period), the decisions were favourable for both traders (buyers and sellers), with no significant losses for buyers and similar gains for sellers.

In general, the results were very successful when using the proposed trading strategy based on the average monthly spot price forecast in the mid-term, showing that the application of this trading strategy in MIBEL was very advantageous, given the relatively low number of bad decisions. The proposed trading strategy can also be analysed for other futures market maturities (weekly, quarterly or yearly) and applied to other electricity derivative markets.

Finally, in the future, given the importance of the forecasting accuracy, to take the correct decisions when traders approach the market options, the purpose will be to refine even further the forecasting model. As such a viable development path entails the use of not only input variables directly related to price information but other relevant external variables that influence electricity markets, such as load and generation forecasting. In addition, the application of other mid-term forecasting models should also be considered, providing a more comprehensive set of forecasting horizons that can not only validate the proposed trading strategy, and even possibly extend it beyond the considered delivery months.

CRediT authorship contribution statement

Bianca G. Magalhães: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Pedro M.R. Bento:** Investigation, Validation, Methodology, Formal analysis, Visualization, Writing – review & editing. **José A.N. Pombo:** Investigation, Methodology, Formal analysis, Visualization, Writing – review & editing. **Maria R.A. Calado:** Investigation, Validation, Supervision, Formal analysis, Visualization, Writing – review & editing. **Sílvio J.P.S. Mariano:** Methodology, Investigation, Supervision, Formal analysis, Visualization, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used in this work are publicly available.

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